Artificial intelligence (AI) and its implications for market knowledge in B2B marketing

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Abstract

Purpose – The purpose of this paper is to explain the technological phenomenon artificial intelligence (AI) and how it can contribute to knowledge-based marketing in B2B. Specifically, this paper describes the foundational building blocks of any artificial intelligence system and their interrelationships. This paper also discusses the implications of the different building blocks with respect to market knowledge in B2B marketing and outlines avenues for future research.

Design/methodology/approach – The paper is conceptual and proposes a framework to explicate the phenomenon AI and its building blocks. It further provides a structured discussion of how AI can contribute to different types of market knowledge critical for B2B marketing: customer knowledge, user knowledge and external market knowledge.

Findings – The paper explains AI from an input–processes–output lens and explicates the six foundational building blocks of any AI system. It also discussed how the combination of the building blocks transforms data into information and knowledge.

Practical implications – Aimed at general marketing executives, rather than AI specialists, this paper explains the phenomenon artificial intelligence, how it works and its relevance for the knowledge-based marketing in B2B firms. The paper highlights illustrative use cases to show how AI can impact B2B marketing functions.

Originality/value – The study conceptualizes the technological phenomenon artificial intelligence from a knowledge management perspective and contributes to the literature on knowledge management in the era of big data. It addresses calls for more scholarly research on AI and B2B marketing.

Keywords B2B marketing, Customer knowledge, Artificial intelligence, Market knowledge, Machine learning, Natural language processing, Knowledge-based marketing, User knowledge

Paper type Conceptual paper

1. Introduction

Scholars from a variety of disciplines agree that businesses are no longer seen from an industrial but from a knowledge perspective (Grant, 1996, 2002; Spender and Grant, 1996). Knowledge, gained from superior information quantity and quality, has become the dominant resource and outpaced physical and financial capital in terms of its organizational importance (Archer-Brown and Kietzmann, 2018; Bollinger and Smith, 2001; Drucker, 1999). Knowledge is also at the heart of market orientation (Day, 1990, 1994, 2000), which has been a dominant marketing paradigm since the 1990s. In particular, market knowledge (Kohli and Jaworski, 1990) is critical for creating offerings that cater to the needs and preferences of customers and for ultimately building and maintaining effective long-term customer relationships. Thus, a systematic knowledge management effort can channel market knowledge into effective B2B marketing strategies and tactics (Shaw *et al.*, 2001).

In recent years, the increasing digitalization and the advent of emerging information and communication technology has transformed value creation in B2B in general (Paschen *et al.*, 2019), and more specifically, how B2B firms manage data and knowledge (Gupta *et al.*, 2017). First, information and communication technologies have fueled the creation of large volumes of data, for example, from the almost ubiquitous use of social media (Kietzmann *et al.*, 2011) and the rise of the Internet of Things (IoT; Osmonbekov and Johnston, 2018; Robson *et al.*, 2016; Turunen *et al.*, 2018). Individually, these new and still emerging data points mean little when compared to their profound joint meaning (Pigni *et al.*, 2016). Collectively, big data, vast in terms of their volume, velocity, variety, veracity and value (known as the Five Vs), are

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becoming an increasingly valuable source for market knowledge for B2B companies.

Second, emerging information technologies can help companies uncover, organize and share the knowledge contained in big data (Codini *et al.*, 2019). One information technology that is gaining increased interest among practitioners is artificial intelligence (Martínez-López and Casillas, 2013; Singh *et al.*, 2019; Syam and Sharma, 2018). As an illustration, a 2018 survey of more than 1,400 B2B marketing executives revealed that the professional services sector ranked among the top sectors to embrace artificial intelligence (MIT Technology Review Insights, 2018). The premise is that, for B2B companies, artificial intelligence can help translate (big) data into information and into knowledge required for developing effective marketing and sales strategies and tactics. Traditionally, this has been a difficult undertaking in B2B marketing, where B2B marketers need to focus on both, understanding customers, i.e. those who make the buying decision, in addition to understanding the users, i.e. those who ultimately use the offering (Abrell *et al.*, 2016). The potential impact that practitioners expect AI to offer to the B2B marketing and sales practice include personalization, customization, innovation and enhanced marketing effectiveness and efficiencies (EverString, 2018).

While marketers acknowledge the opportunities for AI-enabled knowledge, there appear to be gaps in comprehensively understanding artificial intelligence and how to operationalize it for B2B marketing processes and decision-making (Martínez-López and Casillas, 2013; Singh *et al.*, 2019; Syam and Sharma, 2018). In other words, when B2B marketers discuss AI, they often refer to and use different terms and concepts, thereby leading to misunderstandings and confusion about what AI can and cannot do. For B2B managers and executives to be able to assess AI properly, a first critical step is to understand what artificial intelligence is, what the different related terms and concepts mean and how they all come together to offer different value propositions to B2B marketing. In addition, there is a gap in our understanding on the implications of AI with respect to market knowledge in a B2B context. Our article addresses both of these gaps. In response to the first, this article describes the foundational building blocks of any artificial intelligence system and their interrelationships, in addition to clarifying AI-terminology that is often used interchangeably in practice. With respect to the second gap, this article discusses the implications for AI with respect to different types of market knowledge in the context of B2B marketing decision making and outlines avenues for future research in this area. In doing so, our article contributes to the literature on AI and B2B marketing from a knowledge perspective while addressing the call for more scholarly work in this area (Martínez-López and Casillas, 2013; Singh *et al.*, 2019; Syam and Sharma, 2018).

The remainder of this article proceeds as follows. Section 2 begins with a conceptual clarification of artificial intelligence systems, grounding the concept in the appropriate literature. Next, we describe the foundational building blocks of artificial intelligence systems and their interrelationships, along with illustrative examples from B2B marketing in Section 3. Section 4 discusses the implications of AI for market knowledge in B2B marketing along with avenues for future scholarly research, before concluding with a summary of implications.

2. Artificial intelligence systems' conceptual foundations

Our exploration of artificial intelligence starts with an examination of the term intelligence, which, in the human context, is defined as a person's ability to learn, to deal with new situations, to understand and handle abstract concepts, and use knowledge to manipulate one's environment (Legg and Hutter, 2007; Sternberg, 2017). In more general terms, intelligence is defined as the ability to perceive and process data, transform data into information and ultimately knowledge and use this knowledge towards goal-directed behavior. Effective adaptation of intelligence draws upon the selective combination of a number of processes, including perceiving one's environment, problem solving, reasoning, learning, memory and acting to achieve goals.

Following extant conceptualizations, we treat artificial intelligence as "computational agents that act *intelligently*" (Poole and Mackworth, 2010, p. 3). This definition departs from previous views that AI is about machines that can display *human-like* intelligence in two important ways. First, it focuses on acting intelligently, which refers to performing the above outlined processes, such as perception, learning, memorizing, reasoning and problem-solving towards goal-directed behavior. Building on the seminal work of Russell and Norvig (2016), this conceptualization measures the performance of artificial intelligence not in terms of fidelity to human behavior, but instead, in terms of an *ideal performance called* rationality (Russell and Norvig, 2016). An AI system is rational if it does the "right thing" given what it knows. A rational view of artificial intelligence suggests that AI acts so as to achieve the best outcome or, when there is uncertainty, the best expected outcome. By distinguishing between human and rational behavior, we are not suggesting that humans are necessarily irrational, but simply note that human behavior sometimes encompasses behavior that may not achieve the best final outcome (Kahnemann and Tversky, 1979). To echo Herbert Simon (1996), human behavior is *boundedly* rational, that is, it is limited by the information we have, our cognitive abilities, and the finite amount of time we have to make decisions.

The second key element in our notion of artificial intelligence is "computational agents". Referring again to Russell and Norvig (2016), in information systems, an agent perceives its environment and acts upon this environment. Human agents perceive through their eyes, ears and other organs, and act using their hands, legs or vocal tracts. Computer agents use sensors, such as cameras, or keystrokes to perceive inputs and act on the environment by writing files, moving objects or displaying output on a screen. Thus, by including the notion of computational agents, we posit that artificial intelligence agents solve problems in practice as opposed to only in principle. It should be noted that every single AI system described here falls into the field of "narrow" AI, rather than "strong" AI. Narrow artificial intelligence describes AI systems that are optimized for a given task. On the other hand, strong AI, also known as "artificial generalize intelligence," is the research and practice of designing systems capable of solving *any* intellectual task,

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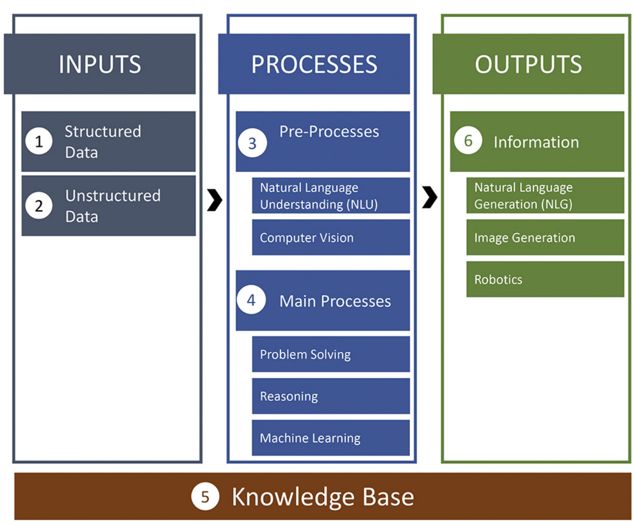
much like a person can. This is extremely difficult, and currently does not exist in practice. The uses of AI discussed in this article focus on narrow artificial intelligence systems.

Information systems, at any level of sophistication or intelligence, consist of hardware (e.g. computers and servers), software (e.g. algorithms), data (e.g. collections of facts and numbers), people (e.g. individuals interacting with various elements of an information system) and procedures (e.g. rules or descriptions for how to use, operate or maintain an information system; Silver *et al.*, 1995). The interaction of an information system with its organizational and social environment follows a basic input–process–output model in which the system itself is seen as a separate entity from its environment. Accordingly, systems require data from human or physical sources in their environment (inputs), manipulate such data in value-creating ways (processes), and feed information (outputs) back to the environment. Regarding their functional relationships, in information systems *data* are treated as raw facts that represent a subject or object in the real world; *information* places these facts into a formative context so that meaning emerges. *Knowledge* develops as we use, question and apply information in useful ways to understand and learn about our environment (Ackoff, 1989).

3. The six building blocks of artificial intelligence systems

The previous section clarified artificial intelligence and information systems conceptually based on the extant literature. Having defined the two key constructs – artificial intelligence and information systems – we can now venture deeper into the concept of artificial intelligence systems. If we accept that (a) artificial intelligence is the theory and practice of developing systems (i.e. machines or computer programs that receive or perceive inputs, process these inputs, and return the results of the processing as outputs) and (b) that these systems act to achieve the best expected outcome, we can unpack AI systems into six building blocks as illustrated in Figure 1: structured data, unstructured data, pre-processes, main processes (i.e. problem solving, reasoning and machine learning), knowledge base and information. The following section offers an introduction to and a definition of each building block (in italics) and discusses each building block's role in AI systems.

Figure 1 Building blocks of artificial intelligence systems



3.1 Inputs

Each information system first must have a means to invite data from its environment to feed its input–process–output transformation. For AI, these inputs come in two forms: structured and unstructured data.

3.1.1 AI building block 1: structured data

Structured data are data that are standardized and organized according to predefined schema. They form the heart of business analytics and business intelligence – activities that are concerned with the methodical exploration of an organization's structured data, often with a strong emphasis on quantitative analyses. Examples include customer demographics, web browsing data or transaction data – all these are internal structured data – and social media ratings or stock exchange transactions, which are examples of external structured data. AI, powered by growing computational efficacy and rapidly improving machine learning techniques (explained in building block 4), is able to run computations on different types of structured data, often in real time.

3.1.2 AI building block 2: unstructured data

Unstructured data are data that are not standardized or organized according to a pre-defined schema. What sets AI apart from traditional information systems is that it can also handle the vastly increasing amount of input data that come in unstructured formats. IoT, social media and mobile devices have led to a seemingly endless flow of digital data that are mostly unstructured and include, among others, human language in written form, such as blogs, posts, reviews, comments or tweets; speech, such as audio in user-generated content, and images that portray objects or people. In a Web form, for example, website visitors may be asked to provide their contact information or give feedback on a product or service by choosing an answer option from pre-determined answer categories (structured data) but also be presented with a comment box in which they can provide additional feedback or questions (unstructured data).

3.2 Processes

Artificial intelligence systems first need to format and standardize unstructured data. These pre-processing activities transform unstructured data into structured data, which can then be manipulated in AI's main processes (building block 4; O'Leary, 2013).

3.2.1 AI building block 3: pre-processes

Pre-processing of unstructured data in their various forms includes data cleaning, normalization, transformation, feature extraction and selection, with the goal that the remaining data can be processed in value-creating ways.

3.2.1.1 Natural language understanding. AI systems use natural language understanding (NLU) to assign meaning to the vast and complicated human language in spoken and written form. Human language comes to life through text (written language) and acoustic signals (spoken language). Before AI systems can make sense of spoken language, speech first needs to be transcribed into text; this step is typically referred to as speech recognition. Although speech recognition and voice recognition are often used synonymously, the former is concerned with detecting the words that are spoken, while the latter identifies the speaker personally. Speech recognition allows an AI system to recognize the words that were said, but not what the words mean. This sense-making takes place as part of natural language understanding. Assigning meaning to written text, i.e. creating a semantic representation of the text, is the most important task in NLU. It is also a challenging task given the ambiguity inherent in natural language resulting from contextual circumstances, linguistic styles or dialog history. For example, artificial intelligence systems need to separate the meaning of homonyms – words with the same spelling and pronunciation, but different meanings (e.g. to *book* a criminal vs to *book* a hotel room), homophones – words that share the same pronunciation, regardless of how they are spelled (e.g. to, too and two) and homographs – words that share the same spelling, regardless of how they are pronounced (e.g. to *tear* up vs to *tear* down). Adding to this complexity of assigning meaning are other issues such as spelling errors, jargon, slang or dialect. Thus, a key task in natural language understanding involves analyzing the syntax (i.e. the structure of sentences), semantics (i.e. the relationship between words, phrases and symbols) and pragmatics (i.e. the context in which words or phrases are used of natural language; Gill, 2019). While early applications of NLU were based on hand-written rules, today's systems rely on machine learning (explained in AI building block 4 below) to extract meaning from text. While several techniques exist, most NLU applications use a lexicon (a vocabulary) and a set of grammar rules coded into its procedures. These applications then use statistical models and machine learning to apply these rules and determine the most-likely meaning of what was said. The applications of NLU today are immense, and include, among others, automatic text summarization, personality insights, sentiment analysis, topic extraction and named entity recognition, i.e. classifying named entities in text into pre-defined categories, parts-of-speech tagging, relationship extraction, or stemming, i.e. reducing inflected words like *fishing* and *fisher* to their word stem *fish*. As an illustration, the start-up firm Klue offers AI-services using natural language processing and machine learning to curate competitive intelligence from written text in 3.5 million external Web sources, processing these data to extract insights for B2B personal selling and sales management. Klue's website promises to provide "a lens for enterprises into their competitor's world, continuously updating and connecting dots to help them win more business." (Klue, 2017). This up-to-date information can better enable sales professionals to answer clients' questions and deposition competitors, in addition to offering valuable insight of what competitors are up to.

3.2.1.2 Computer vision. Computer vision is the transformation of visual images into internal representations of the world so that these representations can interface with other building blocks in the AI system. The degree of sophistication in computer vision varies widely, from recognizing edges or texture to boundaries, surfaces and volumes to the classification of objects, scenes or events (Forsyth and Ponce, 2011). For example, retail technology company Cloverleaf uses AI-enabled computer vision to measure shopper sentiment via store shelves and identify improved pricing or promotion tactics, often in real-time. While easy for humans, visual processing is a highly challenging task for computers and thereby poses a bottleneck for AI systems, which need to work from the resulting output.

Computer vision is strongly linked to the field of machine learning explained in the following section, which provides the algorithmic backend to recognize patterns in and extract meaning from pixels. eBay, for instance, is rolling out a feature that allows users to identify an item found on any website – a blog post or Pinterest – and find similar items on the digital marketplace site by sharing the URL with eBay. Users will also be able to zoom in on specific items within a photo and search for those. While early computer vision systems worked on hand-crafted, human-designed features, today's object classification systems rival human recognition rates.

3.2.2 AI building block 4: main processes

One of the key processes of intelligence is the ability to apply logic to solve problems and learn. Learning is the process of acquiring new or modifying existing knowledge to better achieve desired outcomes. In AI, building block 4 is primarily concerned with three main processes of intelligent behavior: Problem solving, reasoning and machine learning, with machine learning using the two former processes to make machines smarter.

3.2.2.1 Problem-solving. Problem-solving involves choosing the best solution from a range of alternatives for reaching a goal. Just like with humans, two fundamentally different problem-solving processes exist for AI systems. In *divergent problem solving*, artificial intelligence systems generate and evaluate alternative solutions for a given problem. The importance here is that there is no single best solution – a host of alternatives can be equally valuable. *Convergent problem-solving*, on the other hand, is concerned with narrowing down alternatives to find a single-best or even correct answer to a problem. For this, the brute force that AI systems can employ to deal with big data is particularly helpful. However, this does not mean that AI problem-solving always explores *all* options to arrive at the optimal solution. Instead, AI often relies on heuristics to reach outcomes that are sufficient for the immediate problem at hand (Tecuci, 2012). For example, when IBM's Watson defeated the human contestants in the TV game show *Jeopardy!* Watson determined a list of answers along with a weighting for each answer reflecting its likelihood (or confidence) of being correct. It then used the ranked list to decide whether to answer the question and the amount of money to bet. In either case, the divergent or convergent problem solutions are stored (discussed in building block 5 – knowledge base) and existing knowledge is updated (discussed in the below section machine learning).

3.2.2.2 Reasoning. Reasoning refers to applying logic to generate conclusions from available data. Put differently, systems reason with the input to develop reasoned conclusions. It is important to note that there is a fundamental difference between traditional reasoning machines, e.g. data automation systems whose reasoning processes calculate inventory levels or process credit card payments, and AI systems that provide capabilities for reasoning under uncertainty. Consequently, AI systems are also thought of as *inference engines*. They apply rules or laws to the data available to deduce information (Wilson and Keil, 2001). While problem-solving was about finding solutions for problems, reasoning is concerned with the type of logic underlying these processes. Here, too, two main kinds of reasoning exist. *Deductive reasoning*, also known as top–down reasoning, formal logic or the scientific method, combines premises, i.e. logical statements that are believed to be true to obtain new conclusions. Accordingly, if the premises are true, so is the conclusion. Theories are tested, and new knowledge is deduced from previous knowledge. For example, IBM Watson Health was fed a large training data set of proteins and used deductive reasoning to identify proteins associated with cardiovascular disease. On the other hand, *inductive reasoning*, also known as bottom–up reasoning, does not use rules but instead attempts to generate general hypotheses from specific observations. The ultimate goal of the AI system is to detect patterns and develop rules that would not only be conclusive for the data at hand, but that can also be applied to future problems or situations. AI applications, for instance, are used to analyze business-internal data to identify potential future regulatory obligations for the business.

3.2.2.3 Machine learning. If the premise of AI is to develop machines that act intelligently, then they need to be able to learn from past attempts. *Machine learning (ML) encompasses techniques that enable computers to learn from experience*, i.e. *progressively improve their performance, without an explicit, pre-defined set of rules that are stored in memory*. Classic supervised machine learning relied on human decision making to define input features and pre-program specific behavior based on which the systems learned. It soon became clear that successful systems would need to learn from experience and derive insight from large amounts of data – without being explicitly re-programmed every time. Advanced versions of machine learning target this question, developing algorithms and statistical methods that are capable to extract (oftentimes implicit) knowledge from data. The advent of deep learning, new graphics processing units (GPU) technology and vast amounts of data now allows algorithms to automatically learn complex features from the data to optimally perform the task that they are trained on. This renders machine learning the most important element of today's AI systems.

The space of learning algorithms is vast and can be separated into supervised methods (i.e. methods that learn from data for which target output is known), unsupervised methods and reinforcement learning. *Supervised learning methods* include computer vision applications, such as object- or speech recognition, where training data are provided together with correct labels from which the computer learns the patterns and develops the rules to be applied to future instances of the same problem. *Unsupervised learning methods* aim at finding structure in high-dimensional data to make it more accessible (e.g. clustering and dimensionality reduction). *Reinforcement learning* tries to teach agents to learn intelligent behavior from their own past experience. In other words, AI systems learn from various sources not only from the structured and unstructured input data, but also from their own processes. To achieve this, machine learning extends content stored in the knowledge base with new concepts or facts and refines its problem-solving and reasoning processes. Thus, machine learning enhances the competence of an AI system to solve a wider range of problems or increases the accuracy with which re-occurring tasks are solved. This can imply efficiency gains, too, in terms of memory consumption or time spent on task.

No up-to-date AI system exists that does not use machine learning as a key mechanism to dynamically alter its behavior in an ever-changing environment. As mentioned above, its ability to learn without being explicitly programmed means that it can make data-driven decisions or predictions by recognizing patterns within large data sets, even across various data sources. For instance, Source Media, a business-to-business media company, uses natural language understanding and machine learning to develop a highly tailored content strategy to nurture and qualify leads. Using structured and unstructured data from third-party providers, its own marketing platforms and internal sources, Source Media creates prospect profiles and segments them based on users' needs and intents. Employing machine learning, the digital media company delivers highly tailored communications, such as personalized website content, white paper downloads or emails, to nurture and qualify leads ("Lytics | Source Media," 2019).

Artificial neural networks (ANNs) are one of the tools used in machine learning. Inspired loosely by the human brain, ANNs consist of a sequence of computational stages, also known as network layers, each of which performs comparably simple calculations on its respective input and passes the results of the computations on to the next layer, deeper in the network (Kietzmann *et al.*, 2019). Although each computation is mathematically simple, the network as a whole has large computational power owing to the cascaded setup, deriving complex mappings from a sequence of simple nonlinear computations (Knight, 2017). As an example, the computational units in the first layer of a network that performs visual object categorization may receive their input from the pixels of an image and test for the existence of simple oriented lines. The next layer then performs its calculations not on the basis of pixels, but on the level of oriented lines, and thereby detects more complex shapes (curves, crosses, etc.). Like this, units deeper in the network become sensitive to increasingly more complex shapes, resulting in units that are best described as conceptual. For instance, units can be activated upon the presence of a dog, irrespective of breed or viewing angle. The output layer of the network then directly corresponds to the probability that the image contains a given category. Because of ever increasing data availability and computational power of GPUs, today, there exist increasingly complex artificial neural networks that include millions of parameters. The term "deep learning" or "deep neural networks" describes this new and powerful breed of ANNs (Yao, 2017). While the above example describes a visual network performing an object categorization task, networks can learn arbitrary input–output relations. For instance, the input can be pixels, as described above, but also sound-waves (e.g. from a video), temperature scores (e.g. from a sensor), laser-scans (e.g. from medical diagnostics), clicks (e.g. from a user navigating a webpage) and many more – the possibilities are endless. The output can also be diverse, ranging from category labels to speech or robot movements (as described in building block 6). ANN and deep learning algorithms have a variety of marketing applications today, including customer segmentation, predictive lead scoring, ad re-targeting or dynamic pricing models.

To recap, deep learning is a sub-field of machine learning. Machine learning uses algorithms to parse data, learn from it and make decisions based on what it has learned without human intervention. Deep learning structures algorithms in network layers to create an artificial neural network that can learn and make intelligent decision on its own.

3.3 Data storage

In intelligent behavior, the fact that experiences influence subsequent behavior is only possible through memory, which stores past data, information or knowledge for future access. AI systems are highly dependent on efficient storage and retrieval of large volumes of data – both in real-time and in data repositories – to solve problems, reason and learn from experience, which leads us to building block 5.

3.3.1 AI building block 5: knowledge base

A knowledge base stores digital representations of aspects of the real world in which these representations operate, for later access. In the 1970s, such storage places were hierarchical or relational databases that contained rows and rows of structured data. Much like today's AI systems, they were repositories that allowed the encoding and decoding, storing and retrieval of information from past computations. In the AI context, however, these representations can be structured data or data from pre-processing, but also information generated by the system itself, about relationships between objects or events, rules or actions (Hayes-Roth *et al.*, 1983) for three main AI processes: problem-solving, machine learning and reasoning. Finally, knowledge obtained via deep learning is also stored. This form of storage is highly implicit, i.e. the stored computations from a single network layer are impossible to interpret without the context of all others. Deep neural networks can therefore be seen as implicit knowledge bases.

3.4 Outputs

Structured and unstructured data, AI building blocks 1 and 2, encompassed accepting sensory input *from* the environment. Building block 3, i.e. pre-processing (natural language understanding and computer vision) and building block 4, main processing (problem-solving, reasoning and machine learning) transformed these inputs in value-creating ways, while the knowledge base (building block 5) stored the resulting information for future purposes. The final building block discussed here entails the AI system's post-processing interface with its environment. In other words, it refers to what happens in the real world after an AI system generated its results. In general terms, these outputs can inform human decision making or become inputs into other information systems that then act on the internal or external environment of the business.

3.4.1 AI building block 6: information

Information results from data being placed into a formative context so that meaning emerges. This information resulting from AI can then be used to support human decision-making. For instance, digital marketing companies employ AI to improve search engine optimization, mapping content to user profiles and models of what Google looks for in a particular topic. This is similar to how traditional search engine optimization (SEO) keyword search works but expands keywords into semantic topics, thus considering many more topics at a more sophisticated depth than humans. Likewise, sentiment analyses, such as "emotion AI," can help marketing managers determine and quantify the attitudes and affective states of customers, information from which educated marketing decisions can be made. For example, marketing agencies and media companies are employing webcams, computer vision and machine learning to determine customers' emotional responses to advertising. The resulting knowledge enables marketers to optimize their media content to the right audiences (e.g. in pretesting ads) or when to stop showing a specific advertisement. In addition to AI-generated information used in human decision-making, AI-generated information is also used for non-human tasks in a variety of business applications.

3.4.1.1 Natural language generation (NLG). While natural language understanding (NLU) focuses on identifying the meaning of written text, natural language generation (NLG) performs the complimentary task*: natural language generation (or text generation) produces written narratives in conversational language as output*. Natural language processing (NLP) is the umbrella term that describes an AI systems ability to understand and identify the meaning of human language (NLU), decide on an appropriate action and create a response delivered in language back to the human (NLG). By using NLG, organizations can turn large data sets or other internal assets into reports and business intelligence insights, thus bringing a new level of understanding to employee and customer relationships. In addition to internal uses, NLG can also bring economies of scale through applications outside of the organization, for instance by using AI to generate content, for example in advertising or journalism.

The written narratives created through NLG can also take the form of an auditory response delivered back to humans; this is referred to as speech generation. For instance, firms are increasingly using chatbots for "conversational commerce," including marketing, customer relationship management and post-purchase customer support. A sophisticated AI-empowered speech generator can handle hard-to-pronounce words, as well as alter its pronunciation based on punctuation. For example, capitalized words are emphasized, as a human speaker would when indicating that a specific word is particularly important. Furthermore, AI applications just recently managed to accurately mimic an individual's voice after learning which sounds go with text as well as learning about the idiosyncrasies of how one talks. Finally, the latest generation of Google Assistant is capable of calling businesses on behalf the phone's owner, engage in two-way conversations and make appointments using a sophisticated, deep-learning-based, speech recognition, reasoning and speech generation system. Equipped with machine translation, the tool will ultimately be able to understand spoken sentences in one language and translate the content and output it in a different language.

3.4.1.2 Image generation. Image generation is the reverse of image recognition: when the AI system is fed an image description, even with missing data, it can create complete images as output. Still in its infancy, this element can complete images in which, for example, the background is missing, can alter a photograph to render it in the style of a famous artist or even create completely novel headshots of non-real people. Also, intelligent computers can now generate images from text descriptions. These drawing bots can deliver significant value to business functions relying heavily on visual imagery. Image generation can improve photographers' image editing process and deliver great benefits to graphics companies with a continuous need for new stock for use in advertising. In addition, architectural renderings or animated movies generated from a written script could be valuable applications of AI-powered image generation.

3.4.1.3 Robotics. While natural language and image generation are outputs that digitally interact with an AI system's environment, robotics refers to the use of information in machines that physically interact with and alter their environment. Intelligent machines navigate and move through a given physical environment, an application particularly useful in environments where work by humans would be too expensive, too dangerous or sheer impossible, such as disaster relief. Recent advancements in the field of robotics have made robots better at picking up novel items in warehouses and displaying fluid, humanlike movement and flexibility. Another application is intelligent conversation agents, such as chatbots. The use of chatbots ranges from engaging in simple conversations with customers, for example, by responding to frequently asked questions or holding more complex dialogues, such as booking appointments on behalf of clients. B2B software company Hubspot, for example, employs a chatbot to generate leads and keep its site visitors engaged. The chatbot is used to capture leads and provides users with more information about its software, in addition to asking the user questions that helps Hubspot qualify visitors either as prospects or current customers. The virtual agent can also re-direct the conversation to a live employee at any time.

4. Implications of artificial intelligence for market knowledge in B2B marketing

Artificial intelligence, as systems that act intelligently, can be used in a combination of any or all of the aforementioned building blocks to help B2B marketers create, organize and use knowledge for a host of marketing decisions. Indeed, at the heart of our argument in this article lies the idea that the inputs-processes-outputs and the use of different AI building blocks within these can help B2B marketers transform data into information and ultimately different types of knowledge. Understanding the different types of knowledge that AI enables is important for practitioners and scholars. For managers, these differences impact how a B2B firm can turn to artificial intelligence to create, organize and share knowledge, i.e. intangible assets and resources that may result in a sustained competitive advantage or superior organizational performance (Grant, 1996, 2002; North and Maier, 2018; Kogut and Zander, 1992). For scholars, construct diversity allows an investigation of how existing theories and extant understanding in the literature may or may not apply to the knowledge enabled by artificial intelligence. Drawing on the concept of market orientation, a central paradigm in the marketing literature, and specifically relying on the seminal work by Kohli and Jaworski (1990), we discuss the implications of artificial intelligence for enabling three different types of market knowledge: customer knowledge, user knowledge and other external market knowledge (Kohli and Jaworski, 1990).

4.1 Customer knowledge

Customers are individuals who purchase a B2B offering, but do not necessarily use it. *Customer knowledge* includes the inventory of and activities for creating, codifying, sharing and applying knowledge about customers, such as the what, how and why of the purchasing decision, and the antecedents and consequences of this purchasing decision (Abrell *et al.*, 2016). Customer knowledge is important for B2B firms as it relates to short-term performance needs of a product or service and can be a valuable resource for improving an offering.

AI can enable customer knowledge in a number of ways, for example, by creating a comprehensive profile of current or potential customers. AI is able to use structured and unstructured data inputs of various types, such as recency, size, frequency and the type of past purchases, current web browsing behavior, psychographic and demographic characteristics and interactions with the firm to create this profile. Using machine learning and predictive algorithms, the resulting profiles of current or potential customers can then be applied to improve customer relationship efforts, and for prospecting of future customers. In addition, AI can enable marketing efficiencies and greater effectiveness at each stage of the B2B sales funnel (Syam and Sharma, 2018). Using predictive models, AI systems can engage in prospect scoring, i.e. evaluating prospects based on their propensity to buy and identifying high-quality leads, a task that typically requires substantial human resources (Järvinen and Taiminen, 2016). During the pre-approach and approach stages, AI can automate some of the more routine tasks, such as scheduling meetings, or answering common questions via chatbots. At the presentation and close stage of the sales funnel, AI-presentation bots can help sales staff create compelling presentations. Further, AI can help overcome objections from customers, for example, by using emotion AI to understand client's responses at this stage, or AI-enabled battlecards to deposition competitors and strengthen the firm's own value proposition. Lastly, AI can make order fulfilment more efficient by automating order processing and using chatbots to automate tasks during follow up.

A number of future research avenues emerge from the above discussion. For example, if AI is supporting or independently performing previously human-performed tasks in the B2B sales process, a fruitful area for future research is to investigate if and how this impacts the role of sales professionals. For instance, what are the effects of AI on a salesperson's knowledge and performance? How will sales professionals react to the codification of their tacit knowledge enabled by AI? Which of the traditional human tasks in sales are conducive to being performed by AI and to what degree? How can AI support customer knowledge transfer among sales professionals? In addition, investigating how AI changes the value creation process for customers in B2B may be a fertile ground for future studies. For example, how can AI facilitate creating, organizing and applying customer knowledge at each stage of the marketing and sales process? How can AI enable a more effective approach to capturing tacit and explicit customer knowledge?

4.2 User knowledge

While customers encompass buyers in a B2B context, users are individuals who consume a B2B firm's product or service and are most likely located further down the value chain of a B2B firm (Abrell *et al.*, 2016). *User knowledge* includes insights about the experience of using an offering, including users' attitudes, values and future needs and wants, as well as any of the firm's activities related to creating and codifying these insights. In the extant literature, user knowledge has been acknowledged as a valuable as it is not only used to help improve existing products and services, but also to enable the B2B firm to successfully adapt to long-term changes in market needs (Abrell *et al.*, 2016). Thus, user knowledge is critical with respect to new product development, innovation and process improvement (Abrell *et al.*, 2017; Abrell *et al.*, 2016; Pedeliento *et al.*, 2018).

AI enables user knowledge in a number of ways. The explosion of social media use and of IoT has led to an influx of big data that AI can process more effectively and efficiently than humans ever could. For example, AI can analyze vast data sets of written and non-written user-generated content on social media platforms which can reveal insights to B2B marketers about user needs, preferences, attitudes and behaviors (Martínez *et al.*, 2016). The AI system IBM Watson, for example, has the capabilities to identify sentiment, emotions, values and attitudes expressed in a piece of text (Biondi *et al.*, 2017; IBM, 2018). These psychographic characteristics can be a valuable source of insight for B2B marketers for innovation and new product development efforts. In addition, AI can be used to identify themes and patterns in users' posts about their use of a product, which can reveal insights about the user experience and point to areas to enhance this experience. Further, the AI-enabled knowledge about users may point to insights of how users creatively alter products and services (Wilson, 2016), which, in turn, can be a valuable resource for product development and innovation efforts.

A number of these customer knowledge research questions can also be relevant avenues for future research of AI and user knowledge. For example, how can AI support the transfer of user knowledge to a B2B firm? How does AI enable an effective inventory and flow of user knowledge in B2B marketing? In addition, given users are located further down the value chain than customers, future studies may investigate how AI impacts the value creation activities for customers and users differently, and how the interaction between the two can be optimized.

4.3 Other market knowledge

Lastly, according to the market orientation paradigm, B2B firms must develop and use other, external *market knowledge*, i.e. intelligence about external market forces and stakeholders, such as competitors, legislators or news organizations, as these external forces may influence customer or user preferences and behaviors (Kohli and Jaworski, 1990).

AI enables external market knowledge, for example by analyzing the vast amount of online content published on social media platforms, blogs or third-party news platforms, to name a few. For example, AI systems using natural language processing and machine learning algorithms are increasingly used to analyze and identify fake news content (Berthon and Pitt, 2018; Horne and Adali, 2017; Paschen, 2019). This is important for marketers as the creation and dissemination of fake news can threaten the viability of a firm's brand (Berthon and Pitt, 2018) and damage its reputation among a firm's customers and users. Thus, marketers are well advised to be vigilant about if and how their brands are associated with fake news to develop effective tactics to manage these threats. In addition, AI can enable B2B marketers develop competitive intelligence, for example, by identifying keywords or themes from competitors' news releases, social media profiles and other unstructured data. This insight can inform a B2B firm's own positioning strategy, help deposition competitors during the sales process and be a valuable resource for new product development.

A number of future research areas arise from the above discussion. First, the research questions raised with respect to customer and user knowledge can also be potential areas for investigation for market knowledge. In addition, future studies could explore how AI can be leveraged to develop market sensing capabilities, how AI will change the value creation processes for users and customers resulting from other external market knowledge or how AI can facilitate external market knowledge, when the external environment undergoes rapid and unforeseen change?

5. Concluding remarks

This article started off by arguing that in this time of enormous transformations fueled by digitalization, information and communication technology, recent advances in artificial intelligence will have significant implications for businesses and B2B marketing specifically. The fundamental impact that artificial intelligence will bring about will be on how AI enables the transformation of vast amounts of data into information and ultimately knowledge. The trouble is, as it is with many emerging technologies, that B2B managers eager to adopt these new technologies are unclear about how they function and what their potential impacts with respect to knowledge management strategies and tactics are.

Against this backdrop, our article explains to marketing managers and executives in B2B organizations the foundational elements of AI systems and their interrelationships. Specifically, our article introduces a framework consisting of six artificial intelligence building blocks and describes the interrelationships of these building blocks, along with current use cases to illustrate the implications of each building block for B2B marketing.

In addition, our article provides a structured discussion of the implications of AI systems for market knowledge in B2B marketing. AI systems can be used in a combination of any or all of the building blocks to help B2B marketers transform data into information and ultimately different types of knowledge: customer knowledge, user knowledge and other external market knowledge. These activities promise to help B2B firms become more market-oriented, specifically by enabling firms to create, organize and apply knowledge about their customers, users and other external market forces. In addition, our article highlights avenues for future research with respect to each of these types of knowledge. We hope that this article offers practical guidance for B2B managers, in addition to inspiring management and marketing scholars to conduct more nuanced research of artificial intelligence in an organizational context.

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